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An Empirical Analysis of the Effects of Climate Variables on National Level Economic Growth

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Abstract

The influence of climate on economic growth is a topic of growing interest. Few studies have investigated the potential role that climate hazards and their cumulative effects have on the growth prospects for a country. Due to the relatively stationary spatial patterns of global climate, some regions and countries are more prone to climate hazards and climate variability than others. This study uses a precipitation index that preserves the spatial and temporal variability of precipitation and differentiates between precipitation maximums (such as floods) and minimums (such as droughts). The authors develop a year and country fixed effects regression model to test the influence of climate variables on measures of economic growth and activity. The results indicate that precipitation extremes (floods and droughts) are the dominant climate influence on economic growth and that the effects are significant and negative. The drought index is associated with a highly significant negative influence on growth of growth domestic product, while the flood index is associated with a negative influence on growth of gross domestic product and lagged effects on growth. Temperature has little significant effect. These results have important implications for economic projections of climate change impacts. In addition, adaptation strategies should give new consideration to the importance of water resources given the identification of precipitation extremes as the key climate influence on historical growth of gross domestic product.

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An Empirical Analysis of the Effects of Climate Variables on National Level Economic Growth

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Introduction

Growing awareness of the possible harmful effects of climate change has focused the attention of policy makers on the potential economic impacts of climate. Economists and climate scientists have made use of the latest model-based projections of changes in temperature and precipitation produced by a suite of general circulation models (GCM) for this purpose. The results of these studies often range from large negative impacts to relatively modest impacts when aggregated at a global scale (e.g., Nordhaus, 2006; Tol, 2002; Nordhaus and Boyer, 2000).

Interestingly, economists and others have been concerned with the link between climate and economic well being well before the recent attention spawned by climate change. In the late 19th century, the British government charged successive scientists in India with predicting the quality of monsoon rains in an attempt to mitigate the devastating effects of drought on the subcontinent. One of these scientists, Sir Gilbert Walker, pioneered the use of correlation coefficients and used them to establish the Southern Oscillation Index (SOI), a pressure differential between Darwin, Australia and Tahiti that still serves as an indicator of the El Nino/Southern Oscillation (ENSO).

In this study, the focus of investigation is the effect of climate variability on human welfare. From an episodic standpoint, the direct effects of a drought on a region or of a flood on a river basin are fairly obvious. These direct effects can be, and often are, quantified in terms of the damage they cause. However, do these effects accumulate and contribute to a general reduction of welfare or a drag on economic growth? Perhaps surprisingly, previous studies do not provide a convincing answer to this question.

Current understanding of the earth’s climate make clear that different regions of the world differ in terms of their mean climate conditions, e.g., the average temperature and precipitation, but also in the variability of the climate. Parts of the world are more prone to large swings in the year to year amount of rainfall they receive, or the average temperature that occurs. As a result, there are places that have higher and in some cases much higher exogenous exposure to droughts and floods.

This result, that parts of the world experience differential exposure to climate variability and damage-causing climate extremes, has important implications for our understanding of how climate affects human welfare and economic growth. If climate variability was distributed equally throughout the world, then one could surmise that evidence of climate effects on welfare or economic growth would be due to endogenous factors within the states where measured, such as the quality of the institutions or the infrastructure. One may then assume that the key climate differences between countries would be limited to their mean conditions, i.e., some places are hotter or dryer than others. When it is clear that climate variability is not equally distributed but in fact is higher in some regions than in others, then one might surmise that this greater degree of variability could cause conditions that were disadvantageous to human welfare and economic growth. In fact, one could conceive of a state where the effects of repeated droughts or floods are so deleterious that it hinders the ability of that state to make the investments necessary to mitigate the effects of climate variability, investments such as infrastructure and weather observation and forecast systems, and so the effect of climate variability relative to its effect in other states is amplified by the variability itself.

In this analysis we attempt to assess whether climate variability is an impediment to economic growth and a contributor to poverty levels in countries where exposure to variability is high. The analysis makes use of a new rainfall statistic that captures climate extremes in rainfall and their spatial extent. The econometric model is applied to national level growth and poverty statistics representing most countries of the world. It builds on a previous study using a similar approach that identified drought as a significant and negative factor influencing poverty levels and GDP growth in Sub-Saharan Africa (Brown et al., 2010). The results of this study will have significant implications for evaluating the costs of climate change and the continuing dialogue on the best means for adapting to climate change. Typically, climate change impact analyses have focused on changes in mean conditions, effectively ignoring the damages or benefits that might be associated with changes in variability. Furthermore, adaptation planning often proceeds without an understanding of the climate effects that have the strongest impact on society. As a result, temperature is usually employed as the lone predictive variable. Through this analysis we provide some evidence that climate variability, and particularly extremes of precipitation, are the factors that should be foremost in adaptation planning.

Review of the Influence of Climate on Economic Development

The reasoning that underpins the hypothesis that climate has had negative effects on economic growth derives from the ample evidence of direct negative impacts of climate extremes on society locally. In the United States, drought has been estimated to be the most costly form of natural disaster, with an annual average cost of $6 – 8 billion (FEMA, 1995). The recent drought gripping California may cost as much as $2 billion this year to that state alone (McKinley, 2009). Drought is also the leading single cause of deaths due to natural disasters, representing 50% of the global total (World Bank, 2005). The devastating impacts of drought have caused massive famines, such as in the 1980s in Ethiopia and 19th century India, and led to mass migration as in the Dust Bowl of the 1930s in the U.S. and repeatedly in Northeast Brazil, and possibly contributed to conflict in the Sudan recently. Floods affect societies in different ways and at different scales of time and space, but with similar devastation. Floods destroy homes and infrastructure, the "physical and social capital of society" (Dasgupta, 2007) and are frequently followed by disease. In China, floods on the Yangtze River in the early 20th century repeatedly killed hundreds of thousands, and flood damages in 1998 were estimated at $30 billion. Damages due to flooding in 1998 on the Ganges and Brahmaputra in India, Bangladesh and Nepal were estimated at $5 billion.

Country-level studies provide evidence that the direct damages due to climate variability can have a significant effect on national economies. An investigation of drought and flood impacts on Ethiopia using an economy-wide model found that their effects reduced economic growth by greater than a third (Grey and Sadoff, 2006). A study of Kenya found that the variability effects due to ENSO between 1997 and 2000 resulted in losses that ranged from 10 – 16% of GDP as a result of the associated floods and droughts (World Bank, 2004).

The direct effects of climate events on a society or a region are straightforward to quantify. There is also evidence of indirect effects on societies due to repeated exposure to climate variability. The most relevant to this analysis is evidence that repeated exposure to climate extremes leads to risk aversion and a counterproductive reduction in investment, leading to a reinforcing negative wealth cycle or "poverty trap" (Dercon, 1996; Barrett and Swallow, 2006). This evidence is largely derived from information gathered at the household and village level. For example, Rosenzweig and Binswanger (1993) studied household wealth, investment choices and rainfall for 6 villages in India and found that risk aversion due to rainfall variability negatively influenced choices, leading to less profitable investments. Farmers are less likely to make investments in fertilizers or high value crops if there's a significant probability that the investment will be lost due to insufficient rainfall or a flood. As a result, there are major opportunity costs imposed by climate variability that impedes their ability to accumulate savings that might see them through the next shock. They remain trapped in a low level subsistence equilibrium. Dercon (2001) identified rainfall shocks (droughts) as the primary reason that households fell into poverty in a study of 6 Ethiopian villages. Income growth was reduced by up to 20% relative to growth without the rainfall variability. The level of wealth was found to play an important role in the climate effect. In a study of six villages in Burkina Faso, the average farmer experienced food shortfalls in one out of five years due to income variability associated with rainfall, while the poorest farmers (bottom quartile in land holdings) experienced shortfalls in four out of five years, and the top quartile had shortfalls in only one of ten years (Carter, 1997). It was estimated that poor farmers forego about 18% of their income to buffer against climate risks, while the better off farmers forego only 0.4% of income buffer risk (Zimmerman and Carter, 2003).

Do the direct and indirect effects of climate variability aggregate to a detectable signal that influences economic growth at the scale of national economies? Few studies address this question directly. Studies that have attempted to quantify the effect of climate on economic growth have almost entirely focused on changes in mean climate conditions (e.g., Nordhaus, 2006; Tol, 2002; Nordhaus and Boyer, 2000). As Nordhaus describes " … current theories and empirical studies of economic growth give short thrift to climate as the basis for differences in the wealth of nations." Other studies, while acknowledging the potential impact of climate and variability, have classified it as a subcomponent of "geography" (Sachs, 2001). Typically approached using a cross-country analysis method, the results were generally unable to specify significant geography effects that could be distinguished from other institutional factors (Rodrik et al., 2004; Sachs, 2003).

A small number of studies have begun to highlight the importance of year to year variability or changes in climate on economic growth. Brown and Lall (2006) used statistics of rainfall and temperature variability in a cross-country analysis of economic level, finding that poor countries tended to have higher levels of precipitation variability. Dell et al. (2009) evaluated the effects of annual variations in precipitation and rainfall over the previous 50 years as a way to estimate potential economic impacts of climate change. Using national level economic and climate data in a global assessment, their results indicated that higher temperatures had negative consequences in poor countries, while there were no climate effects in wealthy countries. The effects in poor countries were not limited to agricultural production, as they found industrial output, investment growth and political stability all to be impacted. Several recent studies have investigated the effects of climate variability on economic growth in Sub-Saharan Africa (SSA), where the largely agrarian based economies may be particularly vulnerable due to low levels of infrastructure and lack of large scale insurance mechanisms. In a review of a wide range of economic data, Christiaensen et al. (2002) found that rainfall variations and ill health have profound effects on poverty, resulting in a need to social provision of protections against such shocks. Barrios et al. (2008) provide a broad overview of the ways in which rainfall affects economic activities in Africa. Their empirical investigations of agricultural production and GDP growth found that the decline in rainfall that occurred between the 1960s and 1990s in much of SSA was a major contributor to the reduced agricultural production rates and growth rates during that period (Barrios et al., 2008). According to their estimates, the rainfall decline accounted for a 9 – 23% drop in per capita GDP in SSA relative to levels without such decline in rainfall.

A common drawback in previous studies that attempt to assess climate impacts empirically is the form of the precipitation data that is used. Since socioeconomic data is most widely available at the national level, climate data must also be aggregated to national spatial scales for use in analysis. Typically, a spatial average of rainfall and temperature over a given country's national borders is used. This averaging introduces a systematic bias in the resulting rainfall and temperature data due to the smoothing effect that averaging causes. The calculation of a spatial average reduces the variability that is present across a country. As a result, it underestimates the climate challenges that countries face, especially for larger countries. The bias is worse for precipitation than for temperature as precipitation tends to be more variable in space.

While the bias may seem trivial, the way in which precipitation anomalies are expected to affect economic indicators amplified its significance. In typical economic systems that might be affected by rainfall, such as agricultural production, small deviations from normal amounts are likely to have minor or negligible impacts, while large deviations may have very large impacts. This nonlinear response makes the use of spatial averaged rainfall problematic. The calculation of a spatial average over a country means a small deviation below the normal rainfall can have the same value as results from a rainfall pattern of large deviation over a small part of the country and normal rainfall over other parts. An extreme example is the case where part of a country experiences drought while other parts receive normal or above normal rainfall. The resulting spatial average may show normal rainfall. In addition, when used in regression analyses, there's an implicit assumption of symmetry in the effects of above normal and below normal rainfall. This assumption is not supported by the evidence of how such anomalies impact society. In addition, previous analyses use calendar year precipitation which is not appropriate in tropical climates where the rainy season occurs over the end of the year, splitting a single season between two years. It is perhaps not surprising that rainfall rarely shows up as a significant explanatory variable when spatial averaging is employed.

This analysis is distinct from previous work in two important ways. First, we explore the effects of climate extremes instead of the mean conditions that were the subject of previous studies. Second, the index used more effectively instruments precipitation variability than the country mean or population weighted mean used in previous studies. In this analysis we employ a precipitation statistic that preserves the spatial signal in rainfall by calculating the percentage of a country that falls below or above thresholds based on deviations from the long term average. In doing so, we also separate and treat independently the effects of positive and negative precipitation anomalies. This allows the nonlinear effects of precipitation variability to be effectively investigated. The statistic, Weighted Anomaly Standardized Precipitation (WASP; Lyon and Barnston, 2006), is discussed below.

Empirical Methods

In this analysis we use fixed effects regressions with economic indicators as dependent variables and climate data as independent variables to attempt to diagnose the economic effects of climate as manifested at the national level. In doing so we utilize a precise measure of precipitation variability that has qualities which make it superior for identifying associated impacts than other methods typically employed, such as spatially averaged or population weighted precipitation. All precipitation and temperature data are extracted from the New et al. (2000) gridded 0.5 degree dataset. Calculation of national temperature and precipitation follow the usual methods of spatially averaging the annual average over the domain of each country. The data are available for 1901 to 2003. The calculation of the WASP indices, which are used to preserve the spatial and temporal variability of precipitation, begins with the calculation of the weighted anomaly standardized precipitation (WASP) time series for each 0.5 degree grid cell. The WASP calculates deviations in monthly precipitation from their long term mean and then sums those anomalies weighted by the average contribution of each month to the annual total, according to the following formula:

$$S_N = \sum_{t=1}^{N} \left(\frac{P_i - \overline{P_i}}{\sigma_i} \right) \frac{\overline{P_i}}{\overline{P_A}} \qquad (1)$$

In (1) P_i and $\overline{P_i}$ are the observed precipitation in the *i*th month and the long term average precipitation for the *i*th month, σ_i is the standard deviation of monthly precipitation for the *i*th month and $\overline{P_A}$ is the mean annual precipitation. The number of months over which the index is calculated is indicated by *N*. We use *N* = 12 to capture annual precipitation anomalies. The WASP is designed such that rainfall anomalies are measured relative to the typical rainfall for a given month. Next, in order to produce a national level value from the gridded values, a threshold level is designated (for example, 1 standard deviation) and the total number of cells above and below those thresholds is counted.

This produces a measure of the portion of a country that is experiencing anomalously dry (WASP(-1)) or wet (WASP(+1)) over the time period measured. The result for WASP(-1) is well correlated with drought indices, such as the Palmer Drought Severity Index which uses precipitation and temperature to measure drought (Alley, 1984). The WASP(+1) index indicates a period of anomalously wet conditions but may not indicate flood events. Floods can occur on short time spans that are not captured by this index which is calculated with monthly data. The WASP(+1) may capture flooding events caused by longer periods of rainy conditions that saturate soils and lead to intense flooding events over shorter time periods. Further details of the creation of the WASP index and its use in climate analyses can be found in Lyons and Barnston (2006).

Fixed effects regressions

To conduct an assessment of countries' historical sensitivities to climate variation, we use the data described above in regressions within several different specifications, including, regressions with country fixed effects, regressions with year and country fixed effects together, regressions with a one-year time lag and country fixed effects, and regressions with a one-year time lag and country and year fixed effects.

For the purposes of this paper we focus on four primary livelihood indicators as our outcome variables: (1) GDP growth, (2) agricultural GDP value added, (3) industrial GDP value added, and (4) poverty headcount ratio at national poverty line (% of population). The data used for this study covers the period 1961 – 2003.

We also perform these regressions using both fixed effects and random effects. The specifications for these regressions are shown below.

Country Fixed effects

Using fixed effects with a linear model, we de-mean the variables to remove the time-invariant unobserved characteristics that are correlated with the other regressors in the equation. In these regressions, such time-invariant characteristics include, for example, the geographical characteristics of a country.

We begin with a basic fixed effects regression using the panel data for all 133 countries included in our sample.

$$Y_{it} = \beta X_{it} + \alpha_i + \epsilon_{it} \qquad i = 1, .., 133 \text{ and } t = 1, \ldots, T$$

where Y_{it} represents a livelihood measure of country i at time t, X_{it} represents climate measures for country i at time t, α_i is the fixed effect and therefore represents the sum of all time-invariant aspects of country i, and ϵ_{it} represents time-variant factors, which are typically not known by the countries before the time period occurs. We can also add controls for other variables, such as mean annual temperature and precipitation for country i. The unobserved country effects are coefficients on dummy variables for each country.

If we could observe all of the time-invariant country characteristics, then we could use a single cross-section regression of the livelihood indicators on the climate variables. But in such situations, we often cannot observe all of the relevant time-invariant country characteristics, and therefore cross-sectional estimates can be inconsistent. This is the benefit of using fixed effects instead of cross-country regressions; we control for the fact that the climate variability might depend (at least to some extent) on the time-invariant characteristics, which would therefore be correlated.

Standard errors are clustered at the country level. Clustering the standard errors at the country-level allows for potential correlation between observations for any given country at different times. Without clustering the standard errors, we may be overstating the relationship, and the significance of such a relationship, between variables included in the analysis.

These regressions are performed for each of the four abovementioned outcome variables: (1) GDP growth, (2) agricultural GDP value added (%), (3) industrial GDP value added (%), and (4) poverty headcount ratio at national poverty line (% of population).

In addition, these regressions are then repeated, using one-year lagged values of independent variables on the right hand side of the equation.

$$Y_{it} = \beta X_{it-1} + \alpha_i + \epsilon_{it-1} \qquad i= 1,.. , 133 \text{ and } t= 1, \ldots, T$$

For example, these regressions estimate the impact of last year's climate conditions on this year's GDP growth.

Country and Year Fixed effects

In these regressions we start with the same base regression as before, but we now add a year effect, Φ_t, to the fixed effects regression described above. Standard errors are clustered at the country level.

$$Y_{it} = \beta X_{it} + \alpha_i + \Phi_t + \epsilon_{it} \qquad i= 1,.. , 133 \text{ and } t= 1, \ldots, T$$

The unobserved year effects are coefficients on dummy variables for each year included in the panel of data. As with the country fixed effects regressions, we repeat these regressions using one-year lagged values of the independent variables on the right hand side of the equation.

Discussion of Results

The regressions of economic statistics were conducted to attempt to identify whether there is evidence of a climate signal on the economic activity indicators of the nations of the world. The results are reported in Tables 1 – 8 and are discussed below. The tables show the regression coefficient and the standard error in parentheses for each climate variable. Statistically significant regression coefficients are indicated with asterisks. Table 1 presents the summary results for each of the dependent variables for the most robust model specification, fixed country and year effects.

GDP per capita growth is the most widely used and available measure of economic growth at the national level. Here the analyses were conducted with data from approximately 180 nations. The most striking result of the analysis of GDP growth is the negative influence of the WASP(-1) (moderate drought) statistic at the 99% level statistical significance. This result was consistent in all regression specifications. Other results varied by specification.

Table 1. Regressions with Country and Year Fixed Effects

Dependent Variables:	GDP_percap_gwth		Ag ValAdd Growth		Ind_ValAdd		Poverty_headcount	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WASP_plus1	-1.82		0.61		-0.15		-2.83	
	(1.08)*		(1.17)		(0.27)		(25.90)	
WASP_minus1	-2.69		-0.85		-0.20		3.28	
	(0.98)***		(1.04)		(0.24)		(18.44)	
Temp	0.08		0.13		0.04		-1.71	
	(0.32)		(0.33)		(0.08)		(2.70)	
WASP_plus1 (lag)		-2.86		0.54		-0.56		104.19
		(1.11)**		(1.18)		(0.27)**		(105.41)
WASP_minus1 (lag)		-1.78		0.87		-0.36		68.67
		(1.01)*		(1.04)		(0.24)		(47.07)
Temp (lag)		-0.06		-0.29		-0.06		15.58
		(0.10)		(0.17)*		(0.08)		(10.53)
Observations	1686	1677	1418	1416	1098	1117	59	57
Countries	133	137	120	125	105	105	42	40
R-squared	0.05	0.07	0.18	0.16	0.05	0.06	0.94	0.88

Notes: Standard errors are clustered at the country level. Standard errors in parentheses * significant at 10%; ** significant at 5%; *** significant at 1%. The WASP_plus1_1, WASP_minus1_1 and Temp_1 variables are lagged by one year.

The results from the specification with fixed country and year effects are presented in Table 2. These are the most robust model specifications and therefore the most meaningful results. The model with temperature and precipitation as the two independent variables showed temperature to be significant at the 95% level and precipitation at the 90% level. Interestingly, the sign of the regression coefficients were positive in both cases. The sign implies that a warmer year coincides with higher economic growth for the countries of the world, and similarly for (more) precipitation. However, when the WASP variables were included, temperature was no longer significant. Instead, the WASP(-1) variable was significant at the 99% confidence level and the WASP(+1) variable was significant at the 90% level. In both cases, the regression coefficients were negative, indicating that a greater area of a country in drought (WASP(-1)) coincided with less (or negative) economic growth,. The coefficients indicate that a 1 % increase in the fraction of a country's area undergoing drought causes a 2.7 reduction in GDP growth for a given year. More area with anomalously high rainfall or flooding (WASP(+1)) also coincided with reduced economic growth. In this case, a 1% increase in the area of a country experiencing high rainfall coincides with a 1.8% reduction in GDP growth. These results support the hypothesis of the economic importance of precipitation extremes.

Table 2: GDP per Capita Growth with Country and Year FE's

Dependent variable: GDP per Capita Growth

	(Precip)	(Temp)	(P, T)	(W+1)	(T,W+1)	(W-1)	(T,W-1)	(T,W-1,W+1)	(W-1,W+1)
Precip	0.01		0.01						
	(0.01)		(0.01)*						
Temp		0.41	0.44		0.28		0.28	0.08	
		(0.21)**	(0.21)**		(0.25)		(0.27)	(0.32)	
WASP_minus1						-2.02	-2.08	-2.67	-2.69
						(0.51)***	(0.52)***	(0.98)***	(0.98)***
WASP_plus1				0.25	0.29			-1.83	-1.82
				(0.52)	(0.52)			(1.08)*	(1.08)*
Observations	4898	4898	4898	2790	2790	2962	2962	1686	1686
Countries	181	181	181	178	178	180	180	133	133
R-squared	0.047	0.048	0.048	0.057	0.057	0.050	0.051	0.053	0.053

Notes: Columns represent model specifications. Standard errors are clustered at the country level. Standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. P = Precipitation; T = Temperature; W+1 = WASP(+1); W-1 = WASP(-1).

The results for the country fixed effects are reported in Table 3. They are similar to the results with country and year fixed effects. With country fixed effects only, events that affect many countries in a given year, say a currency crisis that affects a region, are not accounted for. However, drought can affect multiple countries in a given year due to its often regional or larger span. For example, droughts caused by ENSO have a global pattern that affects different parts of most continents. Controlling for year fixed effects may cause an underestimation of the drought effect. Therefore, we generate these results with only country fixed effects.

Again, the WASP variables were significant with signs that were consistent with expectations. The WASP(-1) variable was again significant at the 99% confidence level. Similarly, WASP(+1) was significant at the 90% level. Each had negative regression coefficients and the WASP(-1) coefficient is larger (-2.9) than when year fixed effects were controlled for. Temperature was not significant when the WASP variables were included. However, when temperature and precipitation were included as the only independent variables, this time precipitation was significant but temperature was not. The regression coefficient for precipitation was positive. This result implies that the significance of national average precipitation and temperature is sensitive to specification and does not provide much confidence in the meaning of the statistical significance.

Table 3: GDP per Capita Growth with Country FE's

Dependent variable: GDP per Capita Growth

	(Precip)	(Temp)	(P, T)	(W+1)	(T,W+1)	(W-1)	(T,W-1)	(T,W-1,W+1)	(W-1,W+1)
Precip	0.01		0.02						
	(0.01)***		(0.01)***						
Temp		0.15	0.18		0.08		0.12		-0.12
		(0.17)	(0.17)		(0.21)		(0.22)		(0.26)
WASP_minus1						-2.19	-2.22	-2.91	-2.88
						(0.51)***	(0.51)***	(0.97)***	(0.98)***
WASP_plus1				0.62	0.63			-1.89	-1.89
				(0.52)	(0.52)			(1.08)*	(1.08)*
Observations	4898	4898	4898	2790	2790	2962	2962	1686	1686
Countries	181	181	181	178	178	180	180	133	133
R-squared	0.001	0.000	0.002	0.001	0.001	0.007	0.007	0.006	0.006

Notes: Columns represent model specifications. Standard errors are clustered at the country level. Standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. P = Precipitation; T = Temperature; W+1 = WASP(+1); W-1 = WASP(-1).

The regressions on the agricultural value added for the nations of the world provided our most difficult interpretation of results. Overall, in our most robust model specification none of the climate variables were statistically significant. In some specifications temperature and the WASP(-1) variable were significant. It is likely due to the selection of agricultural valued added as the dependent variable. Since this is a percent of a nation's GDP, its value can increase even when actual agricultural GDP decreases if total GDP decreases at a greater rate. For these reason we present these results with caution.

With fixed effects for the country and the year (Table 4), the results of regression on temperature and precipitation as the independent variables showed temperature to be significant at the 95% confidence level. Somewhat strangely, in this case the regression coefficient was negative, which is opposite in direction to the effect on per capita GDP growth. When the WASP(-1) variable is included with temperature, the WASP variable is significant at the 95% level while temperature is no longer significant. The sign of the regression coefficient for the WASP(-1) variable is again negative, which is consistent through all model specifications. When the WASP(+1) is included with WASP(-1) and temperature, none of the variables retain their significance. This is the result reported in summary Table 1.

Table 4: Agricultural Value Added with Country and Year FE's

Dependent variable: Agricultural Value Added

	(Precip)	(Temp)	(P, T)	(W+1)	(T,W+1)	(W-1)	(T,W-1)	(T,W-1,W+1)	(W-1,W+1)
Precip	0.01		0.01						
	(0.00)*		(0.00)						
Temp		-0.45	-0.44		-0.15		-0.13		0.13
		(0.19)**	(0.19)**		(0.26)		(0.26)		(0.33)
WASP_minus1						-1.19	-1.17	-0.83	-0.85
						(0.47)**	(0.48)**	(1.04)	(1.04)
WASP_plus1				0.55	0.54			0.60	0.61
				(0.54)	(0.54)			(1.17)	(1.17)
Observations	4286	4286	4286	2360	2360	2523	2523	1418	1418
Countries	171	171	171	166	166	167	167	120	120
R-squared	0.152	0.153	0.153	0.155	0.155	0.188	0.188	0.177	0.177

Notes: Columns represent model specifications. Standard errors are clustered at the country level. Standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. P = Precipitation; T = Temperature; W+1 = WASP(+1); W-1 = WASP(-1).

In the case of fixed effects for country only (Table 5), here temperature is the one significant climate variable through all specifications. Again, the regression coefficient sign is negative, which is not consistent with the per capita GDP growth results. This result may be caused by an increasing trend in temperature and a generally decreasing percent of GDP that agriculture plays in most economies. For this reason, and since temperature was not significant in the more robust model specification when the WASP variables were included, we do not conclude that there is a meaningful temperature result.

The regression analysis using industrial value added and poverty headcount as the dependent variables did not yield any statistically significant results (Not reported here). In the case of industrial value added this represents a marked difference with the findings of the Sub Saharan Africa – only analysis. In that case, industrial value added was sensitive to drought. The large percentage of electricity generated through hydroelectricity, and the portion of industrial activity that is related to agriculture are the likely causative links. However, using the global dataset the wide heterogeneity of industrial activity and energy sources reduces the effects of climate on industry in most developed countries.

Table 5: Agricultural Value Added with Country FE's

Dependent variable: Agricultural Value Added

	(Precip)	(Temp)	(P, T)	(W+1)	(T,W+1)	(W-1)	(T,W-1)	(T,W-1,W+1)	(W-1,W+1)
Precip	0.01		0.01						
	(0.00)**		(0.00)						
Temp		-2.32	-2.31		-2.10		-2.35		-1.98
		(0.17)***	(0.17)***		(0.22)***		(0.22)***		(0.28)***
WASP_minus1						-1.18	-0.75	-0.48	-0.16
						(0.51)**	(0.50)	(1.11)	(1.09)
WASP_plus1				0.31	0.23			0.41	0.50
				(0.58)	(0.56)			(1.26)	(1.23)
Observations	4286	4286	4286	2360	2360	2523	2523	1418	1418
Countries	171	171	171	166	166	167	167	120	120
R-squared	0.001	0.045	0.046	0.000	0.040	0.002	0.048	0.000	0.038

Notes: Columns represent model specifications. Standard errors are clustered at the country level. Standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. P = Precipitation; T = Temperature; W+1 = WASP(+1); W-1 = WASP(-1).

The analysis of poverty headcount was not informative due to the small sample size (Not reported here). For most countries only a small number of observations were available.

Lagged regression analyses were conducted using the data for dependent variables for the year that follows the values of the independent variables. These analyses are an attempt to identify impacts that might be delayed in their effect on economic activities. For example, when a drought hits, a household may be able to maintain a portion of their consumption through the year of the drought through accessing some form of savings. But in smoothing consumption in the current year there is a negative impact in their productivity in the following year. It may be a reduction in their ability to invest in productive activities (e.g., fertilizer or other inputs) or a reduced appetite for investment after suffering a year of loss. Therefore, the impacts of a climate anomaly such as drought may be expected to affect the current year and the following year's economic activities negatively. This effect is investigated through the lagged regressions.

Table 6a: Lagged GDP per Capita Growth With Country and Year FE's

Dependent variable: GDP per Capita Growth

	(Precip)	(Temp)	(P, T)	(W+1)	(T,W+1)	(W-1)	(T,W-1)	(T,W-1,W+1)	(W-1,W+1)
Precip_1	-0.00		-0.01						
	(0.00)		(0.00)						
Temp_1		0.05	0.06		0.10		0.01		-0.06
		(0.05)	(0.05)		(0.08)		(0.07)		(0.10)
WASP_minus1 (lag)						0.48	0.48	-1.82	-1.78
						(0.47)	(0.47)	(1.00)*	(1.01)*
WASP_plus1 (lag)				-0.42	-0.38			-2.90	-2.86
				(0.54)	(0.54)			(1.11)***	(1.11)**
Observations	4897	4897	4897	2782	2782	2955	2955	1677	1677
Countries	181	181	181	178	178	180	180	137	137
R-squared	0.047	0.047	0.048	0.048	0.049	0.065	0.065	0.065	0.065

Notes: Columns represent model specifications. Standard errors are clustered at the country level. Standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. P = Precipitation; T = Temperature; W+1 = WASP(+1); W-1 = WASP(-1).

In general, the results of the lagged regressions are consistent with the results of the simultaneous regressions. For per capita GDP growth (Table 6), the WASP variables, both drought and flood, were the sole statistically significant factors. The signs of the regression coefficients were negative in all cases, another sign of consistency. The results for WASP(+1) were slightly stronger (99%) than for WASP(-1) (90%) in the lagged regressions, a reversal in ordering from the concurrent regressions. This result may indicate that flood effects, which WASP(+1) may be indicative of, have greater longer term effects due to their destructive capacity. For example, while a drought may reduce savings and investment, a flood can destroy all savings and capital, damage infrastructure such as roadways and contribute to disease such as cholera. All told, these impacts may have longer term effects on economic activities than a drought.

Table 6b: Lagged GDP per Capita Growth with Country FE's

Dependent variable: GDP per Capita Growth

	(Precip)	(Temp)	(P, T)	(W+1)	(T,W+1)	(W-1)	(T,W-1)	(T,W-1,W+1)	(W-1,W+1)
Precip_1	-0.00		-0.00						
	(0.00)		(0.00)						
Temp_1		0.04	0.04		0.05		0.01		-0.01
		(0.05)	(0.05)		(0.07)		(0.07)		(0.10)
WASP_minus1 (lag)						0.35	0.34	-2.20	-2.19
						(0.47)	(0.48)	(1.01)**	(1.01)**
WASP_plus1 (lag)				-0.23	-0.22			-2.64	-2.63
				(0.54)	(0.55)			(1.12)**	(1.12)**
Observations	4897	4897	4897	2782	2782	2955	2955	1677	1677
Countries	181	181	181	178	178	180	180	137	137
R-squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.005

Notes: Columns represent model specifications. Standard errors are clustered at the country level. Standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. P = Precipitation; T = Temperature; W+1 = WASP(+1); W-1 = WASP(-1). The WASP_plus1_1, WASP_minus1_1 and Temp_1 variables are lagged by one year.

The lagged regression results for agricultural value added (Table 7) were also generally consistent with the concurrent regressions. Here, however, temperature was weakly significant (90% level) while no other variables were significant. The sign of the regression coefficient for agriculture was negative, implying higher temperatures coincide with lower agricultural value added. It is difficult to explain how a temperature effect would have a lagged impact but it may be a result of a trend present in the temperature variable. For example, it is well known that global temperatures are increasing measured globally, and the same is true regionally and for most countries. With this trend in place, any trend in agricultural value added will appear correlated with the temperature trend, although it may be caused by other factors such as the decreasing role of agriculture in the economies of many industrialized countries.

The strong significance of the WASP variables in the concurrent regressions may have masked this effect, but in the lagged regressions it stands out as the only significant explanatory variable.

Table 7a: Lagged Agricultural Value Added With Country and Year FE's

Dependent variable: Agricultural Value Added

	(Precip)	(Temp)	(P, T)	(W+1)	(T,W+1)	(W-1)	(T,W-1)	(T,W-1,W+1)	(W-1,W+1)
Precip_1	0.01		0.01						
	(0.00)**		(0.00)**						
Temp_1		-0.04	-0.06		-0.21		-0.03		-0.29
		(0.06)	(0.06)		(0.10)**		(0.09)		(0.17)*
WASP_minus1 (lag)						-0.80	-0.79	0.73	0.87
						(0.47)*	(0.48)*	(1.04)	(1.04)
WASP_plus1 (lag)				0.49	0.40			0.44	0.54
				(0.52)	(0.53)			(1.18)	(1.18)
Observations	4286	4286	4286	2352	2352	2528	2528	1416	1416
Countries	171	171	171	166	166	169	169	125	125
R-squared	0.152	0.152	0.153	0.150	0.152	0.175	0.175	0.160	0.162

Notes: Columns represent model specifications. Standard errors are clustered at the country level. Standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. P = Precipitation; T = Temperature; W+1 = WASP(+1); W-1 = WASP(-1). The WASP_plus1_1, WASP_minus1_1 and Temp_1 variables are lagged by one year.

Table 7b: Lagged Agricultural Value Added with Country FE's

Dependent variable: Agricultural Value Added

	(Precip)	(Temp)	(P, T)	(W+1)	(T,W+1)	(W-1)	(T,W-1)		(T,W-1,W+1)	(W-1,W+1)	
Precip_1	0.01		0.01								
	(0.00)**		(0.00)***								
Temp_1		-0.34	-0.37		-0.64		-0.44			-0.81	
		(0.06)***	(0.06)***		(0.09)***		(0.10)***			(0.16)***	
WASP_minus1_1							-0.72	-0.61		1.40	1.71
						(0.51)	(0.51)		(1.10)	(1.09)	
WASP_plus1_1				0.35	0.13				0.14	0.55	
				(0.55)	(0.55)				(1.25)	(1.24)	
Observations	4286	4286	4286	2352	2352	2528	2528		1416	1416	
Countries	171	171	171	166	166	169	169		125	125	
R-squared	0.001	0.008	0.010	0.000	0.022	0.001	0.010		0.001	0.022	

Notes: Columns represent model specifications. Standard errors are clustered at the country level. Standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. P = Precipitation; T = Temperature; W+1 = WASP(+1); W-1 = WASP(-1). The WASP_plus1_1, WASP_minus1_1 and Temp_1 variables are lagged by one year.

The lagged regressions with industrial value added provide further credence to the impacts of flood on economic activities (Table 8). Here the WASP(+1) variable stands out as the sole significant explanatory climate variable over all model specifications. It is significant at the 95% level and the regression coefficients are all negative. Damage to capital and infrastructure is likely the cause of the negative impact of excessive rainfall. This result is especially significant given the large body of anecdotal evidence of major flood damages and expected economic effects and yet the nonexistent evidence of these effects in any multi-country econometric analyses. This is due to the lack of a consistent database of flood events and flood hazard exposure that is climate based. Instead, existing flood databases are collected by impacts and thus are biased in reporting flood significance not by their hydrologic magnitude, which is largely exogenous, but rather by their economic or social impact, which is largely endogenous. As a result, the economic effects of flood risk and effects are likely underestimated in the literature. This result is the first that the authors are aware of that demonstrates a statistically significant flood effect on national level economic variables in a multi-country analysis.

Table 8a: Lagged Industrial Value Added With Country and Year FE's

Dependent variable: Industrial Value Added

	(Precip)	(Temp)	(P, T)	(W+1)	(T,W+1)	(W-1)	(T,W-1)		(T,W-1,W+1)	(W-1,W+1)	
Precip_1	-0.00		-0.00								
	(0.00)		(0.00)								
Temp_1		-0.03	-0.03		-0.07		-0.07			-0.06	
		(0.05)	(0.05)		(0.06)		(0.06)			(0.08)	
WASP_minus1_1							-0.07	-0.06		-0.38	-0.36
						(0.11)	(0.11)		(0.24)	(0.24)	
WASP_plus1_1				-0.28	-0.29				-0.55	-0.56	
				(0.13)**	(0.13)**				(0.27)**	(0.27)**	
Observations	2760	2760	2760	1737	1737	1830	1830		1117	1117	
Countries	129	129	129	127	127	126	126		105	105	
R-squared	0.049	0.049	0.050	0.059	0.060	0.046	0.047		0.061	0.062	

Notes: Columns represent model specifications. Standard errors are clustered at the country level. Standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. P = Precipitation; T = Temperature; W+1 = WASP(+1); W-1 = WASP(-1). The WASP_plus1_1, WASP_minus1_1 and Temp_1 variables are lagged by one year.

Table 8b: Lagged Industrial Value Added with Country FE’s

Dependent variable: Industrial Value Added

	(Precip)	(Temp)	(P, T)	(W+1)	(T,W+1)	(W-1)	(T,W-1)		(T,W-1,W+1)	(W-1,W+1)	
Precip_1	-0.00		-0.00								
	(0.00)		(0.00)								
Temp_1		-0.00	-0.01		-0.01		-0.06			-0.04	
		(0.04)	(0.04)		(0.05)		(0.05)			(0.07)	
WASP_minus1_1							-0.09	-0.08		-0.35	-0.34
						(0.11)	(0.11)		(0.24)	(0.24)	
WASP_plus1_1				-0.27	-0.27				-0.55	-0.54	
				(0.13)**	(0.13)**				(0.27)**	(0.27)**	
Observations	2760	2760	2760	1737	1737	1830	1830		1117	1117	
Countries	129	129	129	127	127	126	126		105	105	
R-squared	0.000	0.000	0.000	0.003	0.003	0.000	0.001		0.005	0.005	

Notes: Columns represent model specifications. Standard errors are clustered at the country level. Standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. P = Precipitation; T = Temperature; W+1 = WASP(+1); W-1 = WASP(-1). The WASP_plus1_1, WASP_minus1_1 and Temp_1 variables are lagged by one year.

Policy Implications

This analysis of climate effects on economic activity benefited from a more precise measure of precipitation variability than has been employed in previous analysis. The current literature is conflicted on the significance climate variables that affect GDP growth. The results of this analysis strongly support the hypothesis that anomalously low rainfall (drought) and anomalously heavy rainfall (possibly associated with flooding) are the key climate effects on GDP growth, overwhelming any temperature effect.

Projections of climate change impacts on GDP growth often utilize projected temperature changes from General Circulation Models (GCM) applied to an estimated temperature effect. The results of this analysis imply that the greater economic impacts from climate change will be due to changes in precipitation variability. Most significantly, an increase in drought area in a country of 1% was found to cause a 2.8% reduction in annual GDP growth rate. Unfortunately, estimates of precipitation from GCM tend to be less skillful than projections of temperature. The projections of mean changes in precipitation are often characterized by wide ranges and in some cases disagreement on the direction of change. The ability to project variability of rainfall is also less skillful than mean projections of temperature or precipitation. Given our findings, it would be very helpful to have increased ability to project future precipitation variability for estimating future impacts of climate change and identifying adaptation priorities.

While estimating future exposure to drought and flood remains problematic, it is clear from these results that historical levels of precipitation variability already impede economic progress. Managing this hydroclimatic risk in the future is likely to be more difficult because of the changing climate conditions that may alter the historical frequency of floods and drought. Traditional engineering methods for designing and managing water resources infrastructure and institutions use the historical hydrologic record as guidance. Our knowledge of climate variability and change implies that this may not be a valid assumption to base water management on in the future. New methods that are able to respond dynamically to evolving climate conditions will be necessary. This is an open and fairly nascent area of research. The results of this analysis imply that it is a quite important one for future economic growth.

Conclusion

The analysis presented in this paper was conducted to identify the influences of climate on economic activities in the countries of the world. Based on previous research and the published literature, precipitation, temperature and statistics of precipitation variability were investigated as explanatory variables in fixed effects regressions of economic activity statistics over several decades. Several model specifications were utilized to increase the robustness of any findings derived from the regression results. The analysis resulted in several significant findings.

The most important result of this analysis is the identification of the WASP(-1) and WASP(+1) variables as the most significant climate factors in the regressions on GDP growth. The results are important for several reasons. First, they contradict the findings of previous studies that identify temperature as the most influential climate variable on GDP growth. Previous studies have used a coarse measure for precipitation that may obscure the precipitation effect. The WASP variables preserve the spatial variability, and the nonlinearity and asymmetry of precipitation effects and hence better capture their impacts on economic activity. Second, the prevailing thinking on climate change presumes that temperature is the key climate impact on economic activities. Estimates of temperature effects on economic growth are typically used in static projections of the economic impacts of climate change. This analysis shows that those projections are likely to be too simplistic. Precipitation variability has a stronger influence on economic growth than temperature. This complicates climate change impact assessments, since much more uncertainty surrounds projections of precipitation than temperature. Finally, these results should influence strategy for adaptation to climate change. These findings indicate that national economies are impeded by precipitation anomalies, periods of too much or too little precipitation. To prevent increasing damage to economic progress as a result of a changing climate, these results imply that adaptation strategies should focus on reducing the negative consequences of precipitation extremes. Hence, security of water resources should be a priority topic for adaptation planning.

Another interesting finding from this analysis was the significant effect of the WASP(+1) variable on GDP growth and on Industrial value added. The WASP(+1) is indicative of excess rainfall that may be associated with flooding. As discussed earlier, flooding is difficult to specify using monthly precipitation data. Unfortunately, there is a lack of globally available daily precipitation or streamflow data that could be used to more precisely describe flood risk for a particular country. Nonetheless, the results of the regression analysis using WASP(+1) are consistent with expectations for a flood effect. The WASP(+1) variable was found to be a significant explanatory variable for GDP growth at a slightly less significance than the WASP(-1) for the concurrent regressions. Interestingly, the effects were stronger for regressions on GDP and industrial value added at a one year lag. In both cases the WASP(+1) was significant at a 95% confidence level. Regression coefficients were consistently negative, implying a negative impact of excess rainfall. The greater lagged effect may imply that the excess rainfall was associated with flooding that impacted infrastructure. The damage to infrastructure then resulted in reduced output in terms of GDP and industrial value added, both of which may be expected to be more dependent on infrastructure than agriculture. This offers the tentative evidence of a flood effect on these variables in a multi-country analysis. Evidence from case studies of individual flood impacts and of single countries is consistent with this finding. However, a better flood index is needed to explore this effect with more confidence.

In sum, this study has found evidence that climate has a statistically significant impact on economic growth of the countries of the world, and precipitation variability, as characterized by the WASP indices, is the most significant effect. These represent new findings with important implications for how we conceive the relationship between climate and economic growth and how we prioritize adaptation activities.

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